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Calculating Willingness-To-Pay As a Function of Biophysical Water Quality and Water Quality Perceptions

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CALCULATING WILLINGNESS-TO-PAY AS A FUNCTION OF BIOPHYSICAL WATER QUALITY AND WATER QUALITY PERCEPTIONS

by

Carlos G. Silva

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in

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ABSTRACT

Calculating Willingness-to-Pay as a Function of Biophysical Water Quality and Water Quality Perceptions

by

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Utah State University, 2014

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When estimating economic value associated with changes in water quality, recreation demand models typically depend upon either (i) biophysical measures of water quality as collected by natural scientists or (ii) the perception of water quality by recreationists. Models based upon biophysical metrics (such as oxygen concentration, pollutant concentrations, Secchi depth measurements, etc.) operate on the assumption that people can perceive and respond to these metrics, or respond to factors that are, indeed, correlated with the biophysical measure. Economists have often estimated willingness-to-pay (WTP) measures associated with unit changes in biophysical measures without examining the degree to which the measures are truly correlated with perceptions. Recreation demand models that are based upon respondents' perceptions of water quality necessarily assume that perceptions correlate well with the measures used by scientists to evaluate water quality.

Again, WTP for unit changes in perceptions have been estimated without examining the relationship to the underlying biophysical measures. The relationship between biophysical metrics and perceptions is rarely addressed, yet it has profound implications for water quality management and policy. Consider a federal or state agency wishing to manage the quality of its waters in an economically efficient way. Through mandated water quality monitoring regulations, an agency may have many years of biophysical measurements, but these measures are in no way linked to people's perceptions of water quality and, thus, to WTP.

Using biophysical measures of water quality and recreation use data recently collected in Utah, this study links technical measures of water quality at a water body to survey respondents' perceptions of water quality at the same site. This approach is akin to estimating an ecological production function wherein biophysical measures are "inputs" to water quality perceptions (the output). Truncated Negative Binomial models of water-based recreation are used to estimate welfare effects of changes in water quality as measured through (i) unit changes in biophysical measures, (ii) unit changes in perceptions, and (iii) unit changes in biophysical as they change perceptions through the ecological production function.

(73 pages)

PUBLIC ABSTRACT

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When estimating economic value associated with changes in water quality, recreation demand models typically depend upon either (i) biophysical measures of water quality as collected by natural scientists or (ii) the perception of water quality by recreationists. Models based upon biophysical metrics (such as oxygen concentration, pollutant concentrations, Secchi depth measurements, etc.) operate on the assumption that people can perceive and respond to these metrics, or respond to factors that are, indeed, correlated with the biophysical measure. Economists have often estimated willingness-to-pay (WTP) measures associated with unit changes in biophysical measures without examining the degree to which the measures are truly correlated with perceptions. Using biophysical measures of water quality and recreation use data recently collected in Utah, this study links technical measures of water quality at a water body to survey respondents' perceptions of water quality at the same site. This approach is akin to estimating an ecological production function wherein biophysical measures are "inputs" to water quality perceptions (the output). Truncated Negative Binomial models of water-based recreation are used to estimate welfare effects of changes in water quality as measured through (i) unit changes in biophysical

measures, (ii) unit changes in perceptions, and (iii) unit changes in biophysical as they change perceptions through the ecological production function.

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INTRODUCTION

As concern with the health of ecosystems and habitats increases, policy makers must consider how changes in environmental policy decisions and management affect the health of ecosystems (Hanley, Barbier, and Barbier, 2009). The growing level of concern with ecosystem services can be seen in academic fields such as ecology and environmental economics where one may observe a rapidly growing literature in recent years. A key aspect of this literature focuses on simply defining the term “ecosystem services” where, generally, all definitions assess the links between the functions of the ecosystems and services that benefit plant and animal populations, particularly as they relate to humans (Barbier, 2011). Fisher and Turner (2008) stated that “ecosystem services are the aspects of ecosystems utilized (actively or passively) to produce human well-being.” Ecosystem functions can be defined as “the capacity of natural processes and components to provide goods and services that satisfy human needs, directly or indirectly” (De Groot, 1992).

While previous research has made significant progress in developing ecological production functions in the areas of pollination of agricultural crops (Kremen et al, 2007) and carbon sequestration (Nelson et al., 2009), the current understanding of ecological production functions for most ecosystem services remains limited (Environmental Protection Agency, 2009). The difficulties in creating a comprehensive framework for integrated assessment and valuation of ecosystem services still remain even after a substantial amount of study (De Groot, Wilson, and Boumans, 2002). Establishing a clear link between ecosystem functions and its benefits has proven challenging, and examining this linkage is a priority research area (Environmental Protection Agency, 2009).

One of the main challenges faced by researchers is the sheer complexity of structures and processes that lead to ecosystem functions. Measuring the value of direct and indirect use of ecosystems is difficult because many ecosystem services are not exchanged in a market (Mendelsohn and Olmstead, 2009). De Groot et al. (2002) state that the first step in simplifying the complex problem is to translate structures and processes into a limited number of ecosystem functions. He advocates dividing ecosystem functions into four main categories: Regulation, Habitat, Production, and Information. Each of these categories is composed of a number of constituent functions. Information functions provide people with services such as the opportunity for cognitive development, the chance to enjoy scenery or outdoor sport activities, or the use of nature for scientific research or as a creative tool. The recreational function, an Information function, can be expressed as the idea that natural ecosystems provide a variety of options for recreational activities such as fishing, swimming and boating. According to De Groot et al. (2002), the demand for natural areas where one can come to rest or recreate will presumably continue to increase, based on population growth, increasing affluence and leisure time.

The goods and services provided by the recreation function differ from those provided by marketed goods. Marketed goods have marginal values that are known by individuals whereas non-market goods and services such as air quality and water quality have values that are often not known by its users. While many recreation sites such as lakes, beaches, rivers and public parks may charge an entrance fee, those fees often do not represent the actual value of the public good but rather a cost associated with staffing and maintaining the site. Economists have devised a number of different methods to calculate the monetary value of non-market goods and services. These methods can be divided into two main groups; Stated Preference (SP) methods and Revealed Preference (RP) methods. In general, SP methods pose direct questions to people regarding the values they hold, where changes in environmental quality are built into hypothetical scenarios. Popular SP techniques include Contingent Valuation and Choice experiments. In contrast, RP approaches find the analyst observing individuals' consumption of goods that differ in the "amount" of environmental quality that is associated with the goods. Popular RP techniques include Hedonic Price Method, Abatement Cost Analysis and Travel Cost Model (TCM).

In this study we will focus on the Recreation function of ecosystem services, using the Travel Cost Model to calculate the value of changes in the recreation services provided by lakes in Utah. We will combine recreation use data collected via mail survey in 2011 with biophysical measures of water quality collected by the Utah Division of Water Quality. The primary goal is to analyze the relationship between the biophysical measures of water quality at Utah lakes, people's perceptions of water quality at those same lakes, and the impact of water quality on trip behavior. Recreation demand models often assume that individuals respond in the same manner to changes in both types of measurement (for example, water clarity as measured technically by Secchi depth, or as a perceived measure, where clarity is estimated by the recreationist) and that the estimated value of changes in water quality should be the same regardless of the measurement. Many economic studies have been conducted under this assumption even though biophysical measures may not easily understood or accurately perceived by general population.

This study estimates recreation trip demand functions using (1) biophysical measures of water clarity and water color and, (2) perceived measures of water clarity and water color. We find recreation demand behavior is statistically unrelated to biophysical measures but that demand is responsive perceived water quality. We then establish a statistical link between biophysical and perception measures by estimating an ecological production function, where the “input” is a biophysical measure and the “output” is perceived water quality. Having established this functional linkage, willingness to pay for a number of hypothesized changes in water quality are presented using the “linked” model. This study adds to the literature by creating a path that associates changes in biophysical measures to changes in perceptions, which then affect individuals’ recreation behavior.

TRAVEL COST MODEL

When individuals decide to use any recreational area, there are associated costs and benefits. The travel cost model is a method used for calculating consumer surplus (CS) values related to environmental services offered by recreation sites. Since it was proposed by Harold Hotelling in 1947 to estimate the recreational value of US national parks, travel cost models have been widely used in environmental economics. In the travel cost model, quantity is measured as the number of trips taken to a site while price is measured by the cost to travel to a specific site. This can help us arrive at the idea that individuals would travel more often to recreational sites that are closer to their home when compared to sites that are further. This can be explained by the knowledge that travel costs associated with closer sites are lower, leading to more trips to such sites. The travel cost model has the same characteristics as a demand function, meaning when price (Travel Cost) increases then quantity (Trips) decreases, *ceteris paribus*. Just as with a standard demand function, the travel cost demand function is downward sloping.

In order to calculate travel cost, economists estimate out of pocket costs, which are generally driving costs associated with driving to and from the site, and the opportunity cost of travel time, which is typically measured using a fraction of the wage rate which can be capture by individual's income (Parsons, 2003). Economists have not agreed on the precise fraction to use, but the literature has adopted values ranging from one-third of the wage to the full wage (Feather and Shaw, 1999).

This leads to the simple single-site travel cost model:

$$r = f\ (tc_r) \tag{1}$$

where r is the number of the trips taken by an individual in a given season to a specific site and tc_r is the trip cost of reaching site. Figure 1 illustrates the travel cost demand, where the horizontal axis measures the number of trips taken and the vertical axis measures the travel cost.

The sum of areas A and B is the total willingness to pay for r^1 trips. Area B $(tc^1 \cdot r^1)$ represents total cost of taking r^1 trips, whereas area A measures consumer surplus, which is also known as the individual's access value for the site. That is, if the site was to close for a season, the individual would lose the value captured in Area A (Parsons, 2003). While this simple model can provide insight into trip-making behavior, other factors are also relevant to individual's decision in whether or not to visit a recreational site.

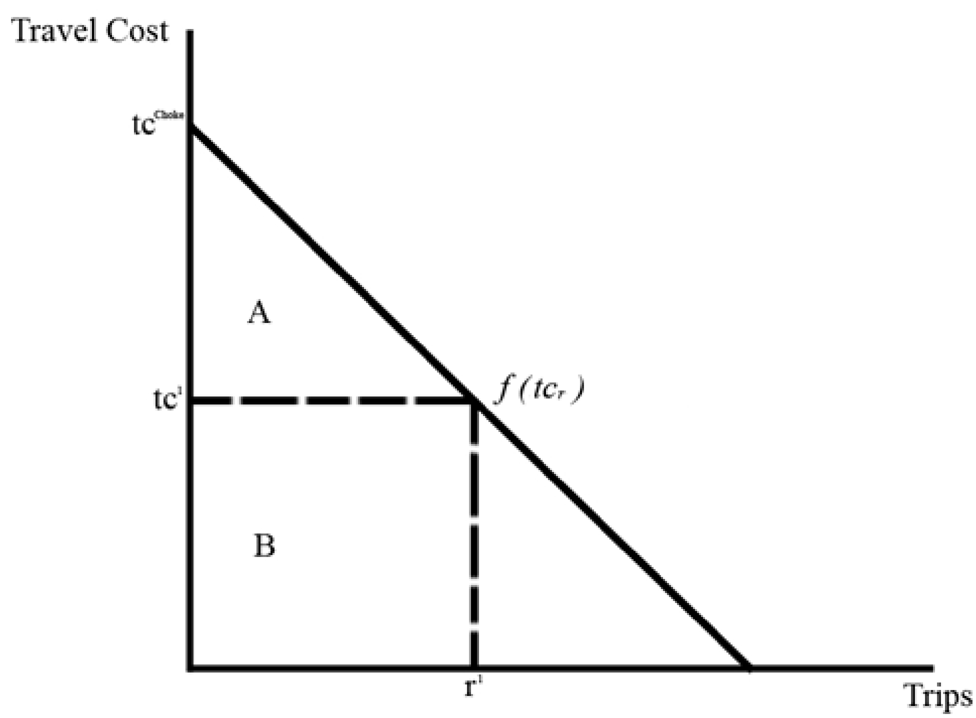

Figure 1 Travel cost demand function

For example, factors such as site quality, income, and distance to substitute recreational sites, may affect trip demand, making trip costs alone a less precise way of estimating demand for recreational sites. Adding these new factors to our previous equation (1) leads to the following:

$$r = f\,(tc_r, tc_s, I, wq_r, z) \tag{2}$$

where tc_r still represents our travel cost to the site, tc_s is a vector of trip costs to substitute recreation sites, I is income, wq_r is water quality at site r, and z is a vector for all other demographic variables that could influence the number of trips (Parsons, 2003). Equation (2) can be written as a linear function,

$$r = \beta_0 + \beta_1 tc_r + \beta_2 tc_s + \beta_3 I + \beta_4 wq_r + \beta_5 z + \varepsilon \tag{3}$$

where the β_i's are coefficients to be estimated using econometric methods, and ε is the error term.

A mathematical approach to measure consumer surplus is given by the integral of the demand curve over price,

$$\Delta\omega = \int_{tc^1}^{tc^{choke}} f\,(tc_r, tc_s, I, wq, z) \tag{4}$$

where, again, tc^1 is the individual's trip cost and tc^{choke} is the choke price. This gives a value equivalent to Area A in figure 1. While in theory we will include the travel cost measures related to substitute sites in our study, we only used the travel cost for the site visited by the respondent. One of the problems with including the price of the substitute sites in a single equation model is that travel costs to many sites tend to be highly correlated. If one decides not to include all sites, the question of which sites should be included as a substitute can also be very challenging. While bias estimates may be a concern with regards of omitting the substitute sites, based on Kling (1989) this issue may not arise. She goes on to state that "if the omitted price is uncorrelated with the included own price, there is no bias to the welfare estimate of either a price or quality change."

As one might expect, changes in site quality can affect the number of trips an individual takes. Envision a scenario where an individual visits a recreational site r^1 times, when water quality level equals wq_r^1 . If all other parameters and variables are constant, what happens when water quality level decreases to wq_r^2 ? The change in wq_r would shift the demand curve to the left, and the individual would take r^2 trips. This effect is shown in figure 2 as a shift from $f\ (tc, wq_r^1)$ to $f(tc, wq_r^2)$, with the corresponding decrease in the number of trips from r^1 to r^2.

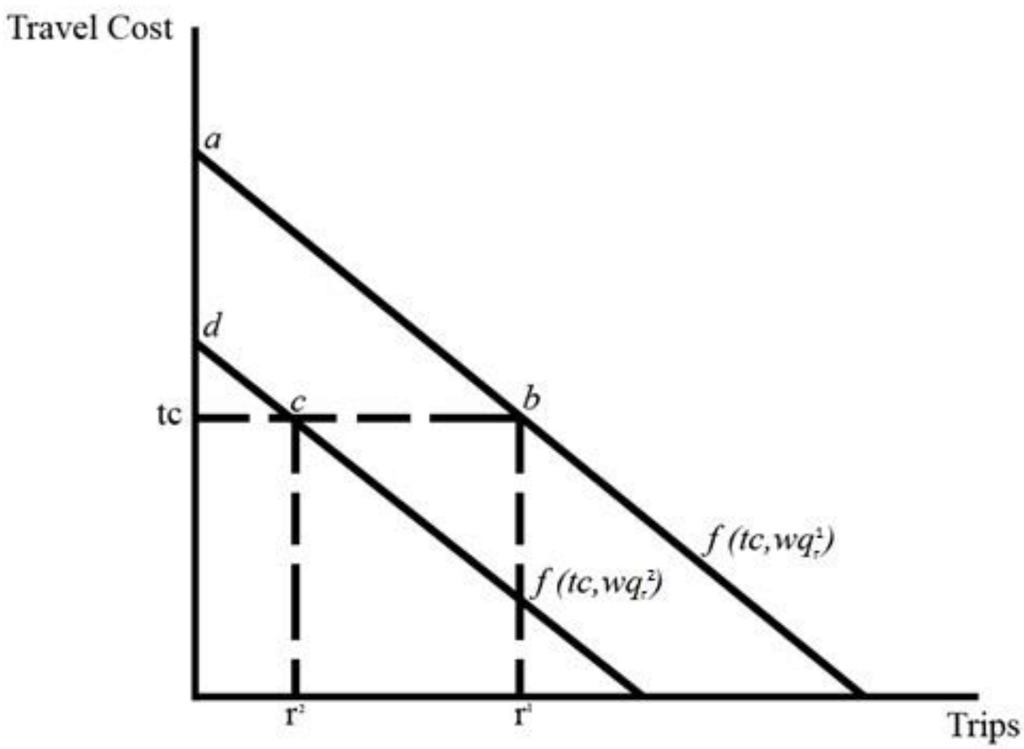

Figure 2 Decreasing water quality

Based on the function *f* (tc, wq_r^1), our original consumer surplus is the triangular area *a-b-tc*. We can see that when water quality decreases to (wq_r^2) the individual will be less satisfied with each visit to the site, leading to r^2 number of trips; this would give the individual a consumer surplus captured by the area *d-c-tc*. The difference between the consumer surplus of these two scenarios will represent the economic loss suffered by the individual as a result of water quality reduction, this loss is captured by the area of *a-b-c-d* (Parsons, 2003).

While water quality is often represented in TCM by biophysical measures, often because these data may be relatively accessible. Studies have shown that individuals' decisions are not only affected by the overall concentration of nutrients but also by their perceptions. One of the early papers analyzing water quality perceptions was written by Bishop, Aukerman, and Connor (1970). In their study, they created a survey where they analyzed four groups of recreationists (swimmers, boaters, fishermen and sightseers) in order to better understand their preferences, the study used psychological research as a basis for better understanding of preferences. The study showed that clarity, cleanliness and color of water can affect the number of trips taking to a site. Looking into how individuals' emotions have a cognitive and behavioral aspect, they were able to recognize that changes in water quality does not have the same level of behavioral response through all groups, with swimmers and anglers more sensitive to perceived water quality problems (e.g., clarity, odor, litter, fish kills, etc.) than boaters or sightseers. The study also shows that individuals will notice poor water quality more often than good water quality, meaning that improvements in lakes with lower water quality would have been more easily perceived by visitors when compared to improvements in lakes with higher water quality. Dinius (1981) used a visual perception test comprised of slides where different levels of litter and dyes were artificially added to water to gauge individual's attitudes towards water bodies with different overall qualities. The litter changed the appearance of the water surface while the dye changed the color. In short, all individuals were presented with five photos, one for each site, where the only change in the water was aesthetic (i.e. litter, discoloration). Using this approach, Dinus found that participants related an increase in litter to a decrease in the actual water quality.

While perception measures are most often qualitative or ordinal variables (e.g., very good, good, bad, very bad); biophysical measures are continuous variables (e.g., nutrient concentration, oxygenation). Without a clear connection between the qualitative variables and the continuous variables, models using such measures could lead to different results. Understanding the connection between the inputs (biophysical) and outputs (perceptions) of an ecosystem function is important for accurate valuation.

ECOLOGICAL PRODUCTION FUNCTION

In the past decade, the number of ecosystem services studies has been rising exponentially (Fisher et al., 2009, p. 643). Services provided by ecosystems are extensive, including biodiversity, resource quality (e.g., drinking water quality), land cover types, resource quantities (e.g., surface water and groundwater availability) and species populations that generate use value (e.g., harvested species and pollinator species) (EPA, 2009). Governmental entities, such as the Environmental Protection Agency have increased their focus on improving tools to value ecosystem services. One such tool is the Ecological Production Function (EPA, p. 30).

An ecological production function (EPF) is similar to the production function, in that the EPF is used to define the relationship between inputs and outputs. In neoclassical theory of the firm a single input production function can be denoted by,

$$y = f\ (x_1) \tag{5}$$

where the function measures the amount of output y that can be produced with x_1 units of input 1. The same concept can be extended to n inputs, leading to the function:

$$y = f\ (x_1, x_2, \dots x_n) \tag{6}$$

In this case the function would measure the maximum amount of output y that can be produced with x_1 units of input 1, x_2 units of input 2, etc. The same practice can be extended to ecological production functions, where the biophysical inputs of an ecological system would provide individuals with services (output). While an ecological production function does not have a specific functional form, one can better understand the ecological production function through a neoclassical production function (figure 3). For example, presence of phosphorous, nitrogen, and some Chlorophyll in a waterbody can be helpful in providing a good overall aquatic health. One can connect the presence of such elements to stage one and two of the production function, where the presence of those inputs (x = nitrogen, phosphorous or chlorophyll) would provide benefits for the aquatic system (output y). As the levels of such elements increase the benefits associate with each unit increase start to diminish. At a certain point a high concentration of these elements (eutrophication) can modify the ecosystem (e.g. fish type) and/or modify other attributes that people perceive (e.g. water clarity, water color). An undesired level of eutrophication can be seen as stage III in a neoclassical production function. One common effect of eutrophication is algal blooms; Chislock et al. (2013) stated that after the death of algal blooms, the microbial decomposition creates anoxic zones ‘dead zones,’ which are areas lacking oxygen to support organisms. According to Carpenter (2005) some of the consequences of eutrophication are excessive plant production, blooms of harmful algae and fish kills; this generates economic losses related to wildlife production, increases the cost of water purification for human use and results in the loss of recreational amenities. The reduction in the number of fish and overall wildlife will eventually lead to a lower number of individuals visiting the lakes. While traditional production function and an EPF are similar, the inputs to an EPF are not fully controlled by humans. An EPF captures the relationship between the biophysical inputs of an ecological system and the services that the system provides (EPA 2009; Boyd and Krupnick, 2013). Another important aspect is that the well-defined relationship between inputs and outputs in a production function is often complex and uncertain in an ecological production function. Many researchers have added to the ecological production function literature over the years, Kremen et al. (2007) were able to create a model that linked changes in ecosystem conditions to the level of pollination of agricultural crops and their yields; they were able to analyze the effect of land use on habitat and foraging behavior pollinators.

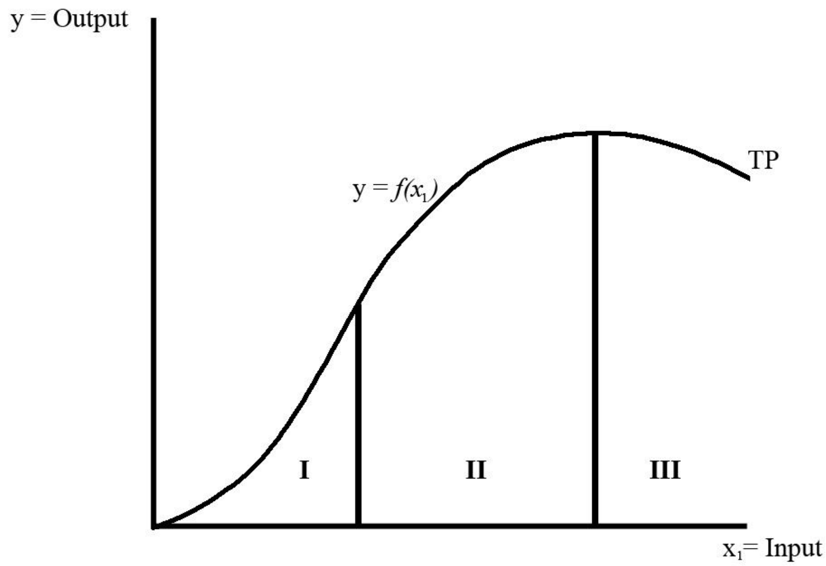

Figure 3 Neoclassical production function

Nelson et al. (2009) used a spatially explicit modeling tool to estimate economic values of ecosystem services, biodiversity conservation and commodities in the Willamette Basin of Oregon. The study used Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) to estimate ecosystem values for three scenarios (Conservation, Plan Trend and Development). The Plan Trend scenario was based on implementation of current policies and recent trends; the Development scenario was based on a loosening of current policies; and the Conservation scenario focused on ecosystem protection and restoration. One of the software's main features is the analysis of how human activities can affect production and value of ecosystem services. The software uses process models to evaluate scenarios and capture the changes in ecosystem services based on an ecological production function approach. Changes in land characteristics over the different scenarios were "mapped" to changes in water service, soil conservation, carbon sequestration, biodiversity conservation and commodity production value. The study takes into account the tradeoffs between the services provided by the ecosystem and compares each scenario overall gains. The researchers concluded that the Conservation scenario produced the largest gains. The value that individuals place on biophysical production of such ecosystem services is a crucial input in such analysis: the authors assumed that all carbon sequestration provided value to all individuals in the world. The authors state: "…clear links need to be made between the biophysical provision [of ecosystem services] and their ultimate use by people."

Since ecological production functions do not have a defined functional form, it can be challenging to illustrate the relationship between the ecological systems and the ecosystem services being analyzed. Providing a functional form to any economic model can be a puzzling task to a researcher. As Griffin, Montgomery, and Rister (1987) have stated, "The researcher … is never in a position to know the true functional form…" noting that, "… the practicing economist makes many decisions in the course of constructing an appropriate model."

An EPF is also useful in understanding how the regulator actions can affect ecosystem services important to the public (EPA 2009). As the EPA stated, "The ecological production function is a critical tool [in]… estimating how the ecological response will affect the provision of ecosystem services" (EPA 2009). Boyd and Krupnick (2013) stated that an "…ecological-production base approach to commodity definition has important implications for the quality and interpretation of stated and revealed willingness to pay

(WTP) estimates." An Ecological Production Function can be used to link the biophysical measures of water quality to one or more ecosystem service end points that can be perceived by the general population. After quantifying the relationship between a biophysical measure and an endpoint, one can include the ecosystem service end point as an independent variable in a valuation model and then analyze the value of those changes (Griffiths et al. 2009).

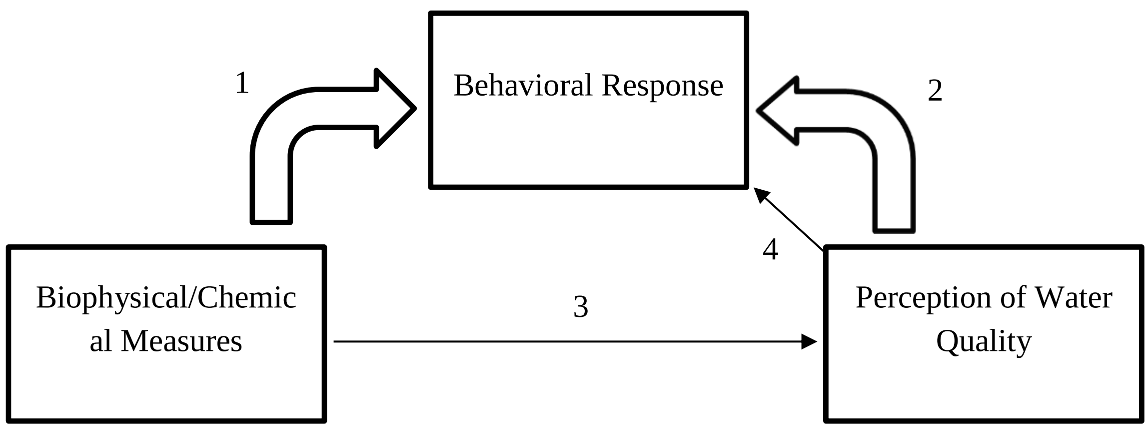

Figure 4 Ecological production function approach

Figure 4 can be helpful in illustrating the models used in this thesis. Arrows one and two (larger arrows) show the conventional models, where the researcher makes a direct connection from changes in biophysical (arrow 1) or perception measures (arrow 2) to the behavioral response. Arrows three and four illustrate the ecological production function approach used in this thesis. In this model, the biophysical measures (e.g. Secchi depth concentration) affect perceptions (arrow 3), and changes in perception would lead to behavioral response (arrow 4), such as the number of trips taken.

METHODS

Ordinary Least Squares

The ordinary least squares (OLS) regression model is one of the most widely used models in economic analysis because of its simplicity and applicability. A general model can be illustrated in matrix form

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{7}$$

where vector **Y** (n x 1) is the dependent variable, **X** (n x k) is representing the explanatory variables, **β** (k x 1) is a vector of parameter to be estimated and **ε** (n x 1) is a vector of error term. The parameters are calculated as:

$$\boldsymbol{\beta} = (\boldsymbol{X'X})^{-1}\boldsymbol{X'Y} \tag{8}$$

As an illustration of our application, the model can be rewritten as:

$$r = \beta_0 + \beta_1 tc_r + \beta_2 tc_s + \beta_3 I + \beta_4 wq_r + \beta_5 z + \varepsilon \tag{9}$$

where ε is the error term; β_s are the estimated parameters of the model, and they describe the directions and strengths of the relationship between *r* (number of trips) and the factors used to determine *r* in the model (Woolridge, 2012).

The classical assumptions about OLS are:

- The regression is linear in parameters, with an additive error term
- The error term is normally distributed with zero mean and constant variance
- The error term is not correlated with the independent variables
- No perfect multicollinearity between independent variables

The recreational data used in this paper is based on nonnegative integer values. Count data models are well suited for this type of data. While in principle we could analyze these data using OLS regression, the use of a distribution that accounts for integer values can improve on OLS model (Greene, 2011).

Poisson

The Poisson model is not based on the assumption that the dependent variable is continuous. While OLS has a normal distribution (figure 5), the Poisson is a non-symmetric distribution defined over non-negative integer values (figure 6), and is well suited for modeling counts of observations. Poisson regression is more appealing than OLS for travel cost demand analysis because people can only take a non-negative integer number of trips to the recreational sites. When the number of trips taken by the individual any given season is assumed to be generated by a Poisson process, the probability of observing the number of trips an individual *i* makes during a season is given by:

$$\Pr(\mathrm{r}_i) = \frac{e^{(-\lambda_i)}{\lambda_i}^{r_i}}{r_i!}\ , \qquad r_i = 0,1,2,\ldots \tag{10}$$

where λ is the expected number of trips, and *r* is the observed number of trips. Similar to equations (3) and (9), λ is assumed to be a function of the variables specified in the demand model. Greene (2011) notes the most common formulation for λ_i is the loglinear model:

$$ln\lambda_i = \mathbf{x}_{\mathrm{i}}'\boldsymbol{\beta} \tag{11}$$

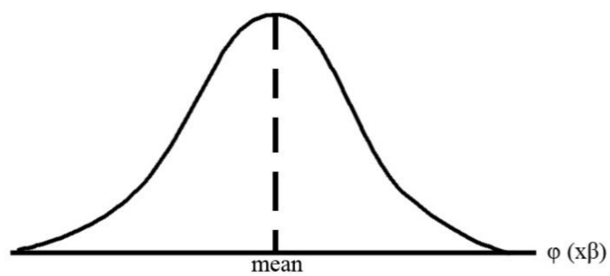

Figure 5 Normal distribution

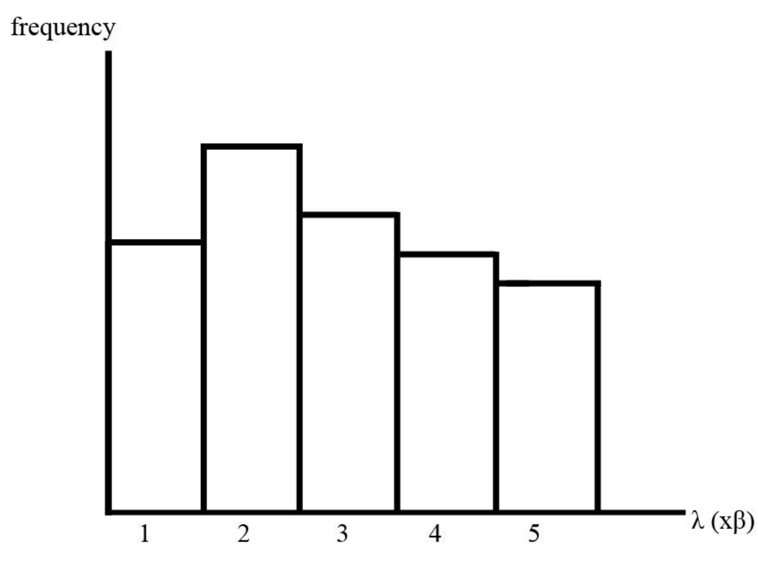

Figure 6 Example of a non-symmetric integer distribution

Similar to equation (9) we can parameterize equation (11) as follow:

$$ln\ (\lambda_i) = \beta_0 + \beta_1 tc_r + \beta_2 tc_s + \beta_3 I + \beta_4 wq + \beta_5 z \qquad (12)$$

Substituting equation (12) into equation (10) yields the probability of observing an individual taking r trips as a function of travel cost to the site, travel cost to other sites, income, water quality and individual characteristics (Parsons, 2003). The model is estimated using the method of maximum likelihood. Cameron and Trivedi (1998) stated that the interpretation of coefficients in Poisson model is different from the OLS model because of its exponentiation; the equation below demonstrates this phenomena:

$$\frac{\partial \mathrm{E}[r_i|\mathbf{x}_i]}{\partial \mathbf{x}_{wqi}} = \exp(\beta_1 + \beta_2 x_{2i} + \beta_k x_{ki}) \times \beta_4 \qquad (13)$$

They go on to state that while a one unit change in the water quality (wq_r) regressor leads to a change in conditional mean by the amount β_{wq} in a linear model, a one unit change in the wq_r regressor in a Poisson model would lead to a change in the conditional mean by an amount of $\mathrm{E}[r_i|\mathbf{x}_i] \times \beta_4$. The Poisson coefficients can be interpreted as "…for a one unit change in the independent variable, the log of dependent variable is expected to change by the value of the regression coefficient" (Piza, 2012).

Negative binomial

A key restriction of the simple Poisson model is that the mean (λ) equals its variance (Greene, 2011). If this assumption does not hold, and the variance is greater than the mean, the model is characterized as "overdispersed". One of the most common models to use when data are overdispersed is the Negative Binomial model. Just as in the Poisson model, the mean of the negative binomial distribution is λ but the variance is $\lambda+(\lambda^2/\alpha)$, where α is the dispersion parameter (Hubbard, n.d.). The probability of observing the number of trips an individual makes during a season is given by:

$$\Pr(r_i) = \left(\frac{\alpha}{\alpha+\lambda_i}\right)^{\alpha} \frac{\Gamma(\alpha+r_i)}{\Gamma(r_i+1)\Gamma(\alpha)} \left(\frac{\lambda_i}{\alpha+\lambda_i}\right)^{r_i} \tag{14}$$

where Γ is the gamma function and, as previously stated, α is the dispersion parameter. Hubbard (n.d.) goes on to state that the negative binomial model is a more general model than the Poisson, as the dispersion parameter (α) gets large while λ is fixed, the negative binomial would converge to a Poisson distribution. We can use the property of the gamma distribution where $\Gamma(\mathrm{n}) = (\mathrm{n}-1)!$ and make a substitution to rewrite equation (14) as:

$$\Pr(r_i) = \frac{\Gamma(\alpha+r_i)}{\Gamma(\alpha)r_i!}(g)^{\alpha}(1-g)^{r} = \frac{{\lambda_i}^{r_i}}{r_i!}\cdot\frac{\Gamma(\alpha+\mathrm{r}_i)}{\Gamma(\alpha)(\alpha+\lambda_i)^{r_i}}\cdot\frac{1}{\left(1+\frac{\lambda_i}{\alpha}\right)^{\alpha}} \tag{15}$$

where

$$g = \frac{\alpha}{\alpha+\lambda_i} \tag{16}$$

Reinstating the fact that we are taking the limit as $\alpha\rightarrow\infty$ holding λ fixed, we arrive at the Poisson model (equation 10).

Truncated negative binomial model

We have one final econometric concern: Our data does not include individuals that take zero trips; this model will be truncated at zero. Based on this we will use the truncated negative binomial model in our analysis of biophysical and perception measures. The negative binomial model allows a positive probability of observing an outcome of zero. In this study we are only concerned with individuals that made trips to the lakes (i.e. integer values equal to or greater than one). To obtain the probability distribution for the truncated negative binomial model, one would need to divide equation (14) by one minus the probability of zero trips, where the probability of zero trips in the negative binomial model will be stated as F_{NB} (0); by doing this we would rescale the old distribution. As stated in Grogger and Carson (1991), "The common statistical structure of truncated estimators follows from the fundamental probability relationship." This relationship is captured in the conditional probability formula. Using that formula, it is possible to calculate the distribution of the truncated probability function by inputting the probability of observing some number of trips in the numerator and the probability of being at or above the truncation limit in the denominator (i.e. one minus the probability of zero trips). Grogger and Carson (1991) illustrated this distribution as:

$$\Pr(Y = r_i | Y > 0) = \frac{\Gamma(r_i + \alpha)}{\Gamma(r_i + 1)\Gamma(\alpha)} \left(\frac{1}{\alpha}\lambda_i\right)^{r_i} \left[1 + \frac{1}{\alpha}\lambda_i\right]^{-(r_i+\alpha)} [1 - F_{NB}(0)]^{-1} \quad (17)$$

DATA

This study dataset came from the Utah's Lakes & Rivers Recreation Survey 2011, organized by the Utah Division of Water Quality. The initial dataset had 1,411 observations. Since this study is concerned with only individuals who participated in water recreation activities in Utah lakes, respondents who stated that they had not visited Utah lakes in the last 12 months were deleted from the dataset (425 observations deleted). Our perceptions data focused on the lake visited most frequently, so respondents who failed to indicate the lake visited most often were also deleted from the dataset (68 observations deleted). Further, individuals with a primary or secondary residence on a lake can affect our calculations because they violate a basic assumption of the travel cost model, which is that trips should not be multipurpose; these observations were also deleted from the dataset (65 observations deleted). The initial dataset was then merged with datasets of travel distance from each zip code to each lake and a set of lake characteristics. Key water quality variables were the Trophic State Index (TSI) for Chlorophyll, Phosphorous and Secchi depth; and the differences between the TSI measure of Chlorophyll and Phosphorous, and the difference between Chlorophyll and Secchi depth[1]. Throughout this paper we will refer to the Trophic State Index for Secchi depth as TSI (SD) and the Trophic State Index for Chlorophyll as TSI(Chla). Six lakes visited by respondents did not have water quality measures, so those observations were also deleted from the dataset (117 observations deleted). We then deleted individuals with incomplete information for the questionnaire questions regarding water clarity and water color perceptions.

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[1] Other characteristics included: elevation (m), surface area (Ha), number of boat ramps, number of campgrounds, fish stock and indicator variables for Blue Ribbon Fishery and State Parks.

We also deleted individuals for whom travel costs could not be estimated because of lack of information (e.g. Income), individuals who were identified to be outliers in our letter value analysis and those individuals that traveled more than 150 miles (one way). This last group was dropped to avoid mixing multipurpose trips and single purpose trips, as well as day trips and overnight trips. The final dataset contain 522 observations. While calculating the travel cost values, the cost of $0.2231 per mile of driving was acquired from AAA (2010). A relatively conservative estimate of 50 miles per hour was used in the calculation of the opportunity cost of time equation. The following table shows the general summary statistics for the dataset of this study.

Table 1 Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Travel cost (U.S. Dollars)	46.0	41.1	2.0	236.6
Number of trips (Per Season)	7.9	9.5	1	80
Income (U.S. Dollars)	80028.7	46104.0	25000	200000
Distance from lake (Miles)	46.5	35.9	2.9	148.7
N				522

Trophic state index

Carlson's (1977) trophic state index is used as the biophysical measure of water clarity and water color. This index uses three different variables that can independently compute algal biomass: Total phosphorous, Secchi depth, and Chlorophyll. In this thesis we only focus on Secchi depth and Chlorophyll measures.

The TSI for Secchi depth can be calculated as follows:

$$\mathrm{TSI(SD)} = 10\left[6 - \frac{\ln Secchi\ Depth}{ln\ 2}\right] \tag{18}$$

where a Secchi depth of 1 meter would yield a TSI value of 60. TSI values based on Chlorophyll micrograms per liter (ug/L) concentration is calculated according to:

$$\mathrm{TSI(Chla)} = 10\left[6 - \frac{2.04 - 0.68 \ln \mathit{Chlorophyll}}{\mathit{ln}\ 2}\right] \tag{19}$$

Here, a concentration of 1 ug/L would yield an index value of 30.6. We may simplify the equations as follows:

$$\mathrm{TSI(SD)} = 60 - 14.41 \ln(\mathrm{SD}) \tag{20}$$

$$\mathrm{TSI(CHL)} = 30.6 + 9.81 \ln(\mathrm{Chla}) \tag{21}$$

The index ranges from 0 to 100, where an increase in TSI of 10 units would be equivalent to reducing Secchi depth by half. With respect to Chlorophyll, its concentration would double with every 7 unit increase in chlorophyll.

Table 2 Summary statistics trophic state index (by Lakes)

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Average TSI(SD)	48.9	10.18	32.1	79.8
Average TSI(Chla)	37.6	11.0	19.8	68.0
N				76

The dataset used contained two different measures for each average and maximum TSI. The average TSI measure was created using multiple measurements throughout the year and across many years. For any given lake the average was computed, this average TSI value will be presented in this thesis as TSI (SD) and TSI (Chla). We do not use the maximum value found for any lake. This represents extreme value that in many cases, occurred years before 2011. Please refer to Appendix 1 for the full table where the summary statistics for TSI (SD) and TSI (Chla) are presented for each lake in the dataset. In using an average over time, we recognize that our TSI contains measurement error thus biasing our TSI variable coefficient toward zero. It is important to note that there while such measurement error exist, there is no variation between TSI (SD) measures within the same lake, the bias from measurement error would make our hypothesis testing results more "conservative."

The table below based on Carlson and Simpson (1996) shows what attributes are expected in a north temperate lake based on different levels of TSI values. The table does not take into account characteristics that tend to vary based on latitude or elevation of the lake.

Relationship between survey and lake trophic status

The survey questions from *Utah's Lakes and Rivers Recreation Survey 2011* were created based on lakes' trophic status. Question 10 captured perceived water depth, and was directly linked to the trophic status of the lake.

10. Which of the following best describes the **water clarity** you usually experienced at this lake this summer?
- O You can see 12 or more feet deep into the water
- O You can see 6 to 12 feet deep into the water
- O You can see 1 to 6 feet deep into the water
- O You can see at most 1 foot deep into the water
- O Don't know

Figure 7 Question 10 extracted from Utah's Lakes & Rivers Recreation Survey 2011

Table 3 Potential changes in north temperate lake based on algal biomass change along the trophic state gradient.

TSI	Chla (ug/L)	SD (m)	TP (ug/L)	Trophic Status	Attributes	Fisheries & Recreation
<30	<0.95	>8	<6	Oligotrophy	Clear water, oxygenated hypolimnion.	Salmonid fisheries dominate
30-40	0.95—2.6	4—8	6—12		Hypolimnion in shallower lakes may become anoxic in summer.	Salmonid fisheries in deep lakes only
40-50	2.6—7.3	2—4	12—24	Mesotrophy	Water moderately clear, but increasing probability of hypolimnetic anoxia in summer.	Hypolimnetic anoxia results in loss of salmonids.
50-60	7.3—20	1—2	24—48	Eutrophy	Decreased transparency, Anoxic hypolimnia during the summer, macrophyte problems may be evident.	Warm-water fisheries only. Bass may dominate.
60-70	20—56	0.5—1	48—96		Blue-green algae dominate during the summer, algal scums probable and macrophyte problems	Nuisance macrophytes, algal scums, and low transparency may discourage swimming and boating.
70-80	56—155	0.25—0.5	96—192	Hypereutrophy	Dense algae and macrophytes during summer	
>80	>155	<0.25	192—384		Algal scums, few macrophytes	Rough fish dominate; summer fish kills possible

Based on Carlson and Simpson, 1996

If we convert feet to meters and use equation 18, each choice would correspond to a range of TSI (SD) values. For example, the first choice (12 or more feet) would correspond to a value less than 41.3 in the TSI (SD) scale. The second choice (six to 12 feet) would range from 41.3 to 51.3. The third choice (one to six feet) would range from 51.3 to 77.1, whereas the fourth choice would imply a TSI (SD) value greater than 77.1. Comparing those values to the ranges given in table 3, we can see that each group is closely connected to a specific Trophic Status (oligotrophic, mesotrophic, eutrophic and hypereutrophic). Based on that, we can recognize that the first choice on question 10 was representing an oligotrophic status, the second choice a mesotrophic status, the third choice represented a eutrophic status and the fourth choice represented hypereutrophic status. In question 10 (figure 7), the first option was coded as 1, second as 2 and so on; participants that chose the option "Don't Know" were coded as missing value. Table 4 shows the percentage distribution for the option choices.

Table 4 Ordinal coding and distribution of survey question 10

Question 10 Option Choice	**Frequency**	**Percentage**
1 (More than 12')	43	8.24%
2 (6' — 12')	116	22.22%
3 (1' — 6')	262	50.19%
4 (Less than 1')	101	19.35%
Total	522	100.0

It is important to note that water clarity has two main components: Materials dissolved in the water and materials suspended in the water (algae and silt); out of those components algae population is usually the one that varies the most (Shaw, Mechenich, and Klessig, 1993). The presence of color in the water may reduce light penetration, which can affect algae growth. Algae decomposition stages may impart a green, brown or even reddish color to the water. Although the human activities can affect lake water quality, all lakes follow a natural aging process which would lead to a change from oligotrophic to eutrophic. Finally, we need to note that, even though changes in color and clarity are perceived differently by different individuals, overall trophic status does not change widely without external influences.

In order to better understand the data, trophic classifications were cross-tabulated against individuals' perceptions of clarity. The first three columns of table 5 recreate portions of Carlson's trophic status. Some 138 respondents visited lakes classified as oligotrophic; these lakes had an average TSI(SD) equal to 34.0 (column 4, table 5). The average "perceived clarity" as measured by Question 10 was 2.5 (column 5). Almost 13% of respondents said clarity was greater than 12 feet; just under 34% said clarity was between six and 12 feet. About 47% reported clarity between one and six feet. Finally, 5.8% of respondents said clarity at oligotrophic lakes was less than one foot. Subsequent rows of table 5 link perceptions to biophysical measures of water quality for lakes classified by the Department of Water Quality as mesotrophic, eutrophic and hypereutrophic. The fact that individuals were interviewed after they have visited the site could lead to confirmation bias related to the overall water quality, perhaps leading respondents to report better clarity than they actually experienced. Based on table 5, such confirmation bias appear to not have a high impact on the overall pattern for the answers in question 10. As one can see there is a pattern that illustrates the fact that individuals appear to be relatively consistent with their perception of water clarity. One can see the pattern in columns 6 through 9: as clarity in a lake declines (the mean TSI(SD) increases) those visiting the lake are less likely to perceive a "clear" lake and more likely to perceive a lake that is much less clear. Table 6 reports similar information for those choosing to visit the most popular lakes in our sample.

The Pearson's chi square test was used to test whether the rows and columns of the clarity response (table 5) are independent. The test rejected the null hypothesis that the rows and columns are independent, this is important since it can show that individuals' perceptions distribution do change with different trophic classifications.

While the question related to water color (question 11) in the lake visited during the summer did not have a direct link to trophic classifications, color perception may be important to understand individuals' trips to lakes. Figure 8 shows the question:

11. Which of the following **shades of green** did the water usually have at this lake this summer?
- No green tint
- Slight greenish tint
- Dark greenish tint
- Don't know

Figure 8 Question 11 extracted from Utah's Lakes & Rivers Recreation Survey 2011

The ordinal coding scheme for question 11 was similar to that of question 10. Just as in the previous question the first option was coded as one, the same process follows for the next choices; participants that chose the option "Don't Know" were coded as missing value. Table 7 shows the percentage distribution for question 11.

Table 5 Tabulation of trophic classification against clarity

TSI	Secchi depth (meters)	Trophic Classifications	Mean TSI(SD)	Mean Perc. Clarity	Responses to Question 10 (Clarity)				N
					> 12 ft	6—12 ft	1—6 ft	< 1 ft	
0-40	>8-4	Oligotrophy	34.0	2.5	13.0%	33.4%	47.8%	5.8%	138
40-50	4-2	Mesotrophic	44.0	2.7	10.6%	24.3%	53.0%	12.1%	198
50-70	2-0.5	Eutrophic	57.4	3.0	3.2%	14.3%	61.9%	20.6%	126
>70	0.5-<0.25	Hypereutrophic	79.6	3.7	0%	6.7%	21.7%	71.6%	60

Table 6 Tabulation observing 10 lakes most visited

Lake	TSI(SD)	Mean Perc. Clarity	Responses to Question 10 (Clarity)				N
			> 12 ft	6—12 ft	1—6 ft	< 1 ft	
Strawberry Reservoir	32.3	2.7	4.3%	31.8%	57.5%	6.4%	47
Bear Lake	34.1	2.4	17.7%	32.3%	43.5%	6.5%	62
Flaming Gorge Res.	36.5	2.4	19.2%	34.6%	38.5%	7.7%	16
East Canyon Reservoir	42.5	2.8	0.0%	33.3%	55.6%	11.1%	18
Deer Creek Reservoir	42.8	2.6	12.9%	22.5%	51.6%	13.0%	31
Rockport Reservoir	43.9	3.1	8.3%	8.3%	50.0%	33.4%	12
Jordanelle Reservoir	44.8	2.9	0.0%	21.0%	68.4%	10.6%	19
Pineview Reservoir	50.4	3	0.0%	19.5%	61.0%	19.5%	41
Willard Bay Reservoir	68.8	3.1	2.9%	8.6%	62.9%	25.7%	35
Utah Lake	79.8	3.6	0.0%	5.6%	24.1%	70.3%	54

Table 7 Ordinal coding and distribution of survey question 11

Question 11 option choice	**Frequency**	**Percentage**
1 (No green tint)	98	18.77%
2 (Slight greenish tint)	296	56.70%
3 (Dark greenish tint)	128	24.53%
Total	522	100.00%

Based on the answers gathered from the survey response it appears that most of the lakes in the survey (81.23%) were perceived to have a greenish tint. It is important to note that the results do not indicate that most lakes have a greenish tint but instead it shows that most of the individuals surveyed perceived some level of greenish tint in the waterbody visited most often.

Three dummy variables for primary recreation activities at lakes were created; one for individuals who stated that boating was their primary activity, one for individuals who fish (warm water fishing and cold water fishing were coded the same) and one for individuals who stated that their primary activity was swimming. All other choices were combined and used as our base activity choice. A respondent saying that boating was their primary activity was coded as a one, and zero if not. The activity variables highlight visitor's whose primary activity involves some contact with the water; our omitted category includes lake visitors whose primary activity did not involve contact with the water.

Summary statistics based on individuals' primary activity are reported in table 8.

7. In the **last 12 months** which **ONE** activity did **YOU** spend the most time doing during your lake visits? *(Choose only one.)*

- O Boating (includes motor-boating, house boating, sailing, canoeing, kayaking, jet skiing)
- O Fishing – warm water fish species (for example, bass, perch, catfish, crappie, sunfish)
- O Fishing – cold water fish species (for example, trout, whitefish, salmon)
- O Swimming (includes playing in the water, wading, windsurfing, water-skiing, tubing)
- O Near-shore activities (includes walking, biking or running on trails, bird/wildlife/nature viewing, picnicking, camping)
- O Hunting – waterfowl
- O Hunting/Trapping – other

Figure 9 Question 7 extracted from Utah's Lakes & Rivers Recreation Survey 2011

Table 8 Summary statistics based on primary activity

Variable	Swimmer			Boater			Angler			Near Shore Activity		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
TSI(SD)	51.43	16.89	54	54.82	15.85	130	45.53	12.20	189	46.36	13.56	149
TSI(Chla)	36.19	12.88	54	40.99	11.70	130	38.72	9.94	189	36.02	12.01	149
Water Clarity (Q10)	2.91	0.83	54	2.95	0.82	130	2.75	0.83	189	2.72	0.87	149
Water Color (Q11)	2.02	0.63	54	2.04	0.63	130	2.10	0.66	189	2.02	0.68	149
Number of Trips (Per Season)	7.29	8.89	54	9.20	11.65	130	8.21	8.82	189	6.54	8.07	149

RESULTS

The travel cost demand literature has generally taken two different paths when including water quality measures in the demand function. One includes biophysical measures of water quality in the demand function assuming that these measures can be perceived, or are highly correlated with outcomes that can be directly observed. The second approach eschews biophysical measures and uses direct measures of water quality perceptions. We will estimate both types of models, and then link individuals' perceptions to biophysical measures. The perception measures chosen were water clarity and water color. Our biophysical measures are two measures of the Trophic State Index (TSI). While this index theoretically has no upper bound, in practice it can range from 0 to 100; where higher values correspond to higher biomass concentration in a waterbody (Carlson, 1977). Our two TSI measures as previously stated, are calculated from Secchi depth and the concentration of Chlorophyll in water.

Prior to running any regressions we examined our survey responses to understand the relationship between water quality and perceptions. Responses to the water color question (Q11) lead one to believe that very green lakes are preferred. The academic literature finds that individuals enjoy lakes that look more "natural" (Smith, Croker, and Farlane, 1995). The authors state that even though blue water is preferred to yellow water, the latter may be acceptable if it is perceived as "natural." This is very important in understanding individuals' preference for certain water color. In our dataset we only take into account the intensity of greenish tint, with no other measure of individuals' water color preference. Taking that limitation into consideration our WTP estimates focus only on changes in water clarity. We do not fully understand visitor's water color preferences, so we have no hypothesis concerning the sign of the water color variable in the demand model.

Modeling Results

Preliminary Poisson modeling indicated that the mean number of trips was not equal to the variance of trips. Using the likelihood-ratio test that alpha (from equation 14) equal to 0, one concludes that alpha is significantly different from zero. This indicates that the simple Poisson should not be used; instead, we adopt the negative binomial regression. Further, the minimum number of trips is one so the appropriate model is the truncated negative binomial.

Table 9 (column 2) provides the estimated parameters for the biophysical model, which attempts to capture how individuals' number of trips can be affected by changes in biophysical measures of water clarity. The perception model (table 9, column 3) shows how the number of trips are affected by perception measures of water quality. With the exception of *Ln (surface area)* which is highly significant in the perception model, all other variables included in both models had the same level of significance and sign. As expected, the *Travel Cost* variable had a negative sign. The data shows that swimmers are not significantly different from individuals whose primary activities did not include contact with the waterbody and that, all else equal both anglers and boaters visit lakes more frequently than swimmers or those who do not contact the water. The ln (alpha) shows that the use of a negative binomial model is appropriate.

In the biophysical model the TSI (Chla) variable had a positive sign, which shows a correlation between higher numbers of trips to lakes with darker greenish tint water body. The TSI (SD) has a negative sign, meaning that individuals respond negatively to increases in TSI (SD). However, both TSI measures are not significant within a 10% confidence level. When comparing the biophysical measures to the perception measures, even though the biophysical variables were not significant within 10% confidence (table 9, column 2), both measures (biophysical and perception) follow the same direction. The Water Clarity variable, which takes into account the answers from Question 10, has a negative sign. That is, individuals appear to enjoy lakes with higher perceived clarity levels. The Water Color variable had a positive sign, which shows a correlation between higher numbers of trips as lakes have a darker greenish tint.

Table 9 Truncated negative binomial results (biophysical & perceptions model) dependent variable: number of trips

Variables	**Biophysical Model**	**Perceptions Model**
Travel Cost	-0.005	-0.005
	(-3.88)***	(-4.31)***
TSI(SD)	-0.006	-
	(-1.06)	-
TSI(Chla)	0.009	-
	(1.25)	-
Water Clarity	-	-0.187
	-	(-2.83)***
Water Color (Green)	-	0.253
	-	(2.93)***
Swimmer	0.146	0.159
	(0.75)	(0.83)
Boater	0.377	0.370
	(2.59)***	(2.57)***
Angler	0.258	0.235
	(1.90)*	(1.78)*
Ln(surface area)	0.041	0.054
	(1.77)*	(2.47)**
Intercept	1.524	1.497
	(5.60)***	(5.37)***
Ln (alpha)	0.301	0.251
	(2.34)**	(1.99)**
N	522	522

* $p<0.1$; ** $p<0.05$; *** $p<0.01$, z-value in parentheses

Our water quality variables (clarity and color) share the same signs across the two models, yet the biophysical measures are statistically insignificant. This indicates that either (1) biophysical measures of water quality are imperfectly perceived by people or, (2) behavioral responses are governed only by perceptions, or both. This creates an issue for those who manage water quality in that the biophysical metrics used to assess water quality do not match up with peoples' perceptions of water quality. If, however, a functional relationship between perception and biophysical measures of water quality can be established then one may use this relationship to link biophysical measures to behavioral response and, thus, measures of consumer surplus.

Linking biophysical measures to perceptions

Given the way in which perceptions were measured, we may use the ordered probit model to link perceptions to biophysical measures. The ordered probit model is based on the idea that there is a qualitative order in the responses being analyzed in the survey. As Greene (2011) shows, the model is built around a latent continuous variable, $y*$ which can be calculated from the following linear combination:

$$y_i{}^* = \boldsymbol{x_i}'\boldsymbol{\beta} + \varepsilon_i \tag{22}$$

y_i is an observed ordinal variable with an indicator outcome of one, two, three, etc, if,

$$y_i = j \quad \text{if } \varrho_{\boldsymbol{j-1}} < y_i{}^* \leq \varrho_j \tag{23}$$

where j=1,…,m and ϱ's are unknown parameters to be estimated. We apply this general model to water quality perceptions, where the responses to the water clarity question (Q10) from question 10 (Clarity) is the observable ordinal dependent variable. We note that y* can be interpreted as an individual's own scale of water clarity, which is unobservable. This individual scale depends on measurable factors x (i.e., the biophysical measures) and other unobservable factors 〖ε〗_. If y* crosses a certain unknown threshold, the individual will report first choice, then second choice and so on. Since there are a limited number of choices, the person chooses the option that is closer to his/her own scale.

We can calculate the probability that individual *i* will select choice *j* based on the equation below:

$$p_{ij} = p(y_i = j) = p(\varrho_{\boldsymbol{j-1}} < y_i^* \le \varrho_j) = F(\varrho_j - \boldsymbol{x_i}'\boldsymbol{\beta}) - F(\varrho_{\boldsymbol{j-1}} - \boldsymbol{x_i}'\boldsymbol{\beta}) \quad (24)$$

where ϱ's are unknown parameters to be estimated with $\boldsymbol{\beta}$, and F is the standard normal cumulative distribution function. Below we have an example of the probabilities for a question with four categories:

$$p(y_i = 1 \mid \boldsymbol{x_i}) = F(\varrho_{\boldsymbol{j}} - \boldsymbol{x_i}'\boldsymbol{\beta}) \quad (25.1)$$

$$p(y_i = 2|\boldsymbol{x_i}) = F(\varrho_{\boldsymbol{j}} - \boldsymbol{x_i}'\boldsymbol{\beta}) - F(\varrho_{\boldsymbol{j-1}} - \boldsymbol{x_i}'\boldsymbol{\beta}) \quad (25.2)$$

$$p(y_i = 3|\boldsymbol{x_i}) = F(\varrho_{\boldsymbol{j}} - \boldsymbol{x_i}'\boldsymbol{\beta}) - F(\varrho_{\boldsymbol{j-1}} - \boldsymbol{x_i}'\boldsymbol{\beta}) \quad (25.3)$$

$$p(y_i = 4 \mid \boldsymbol{x_i}) = 1 - F(\varrho_{\boldsymbol{j-1}} - \boldsymbol{x_i}'\boldsymbol{\beta}) \quad (25.4)$$

The ordered probit output for Water Clarity as a function of TSI(SD) and Water Color as a function of TSI(Chla) are given in table 10.

Table 10 Linking biophysical metrics of water quality to perceptions

Perception Measure	Clarity	Color (Green)
TSI(SD)	0.038	-
	(10.26)***	-
TSI (Chla)	-	0.013
	-	(3.02)***
ϱ_2	0.286	-0.396
	(1.58)	(-2.28)**
ϱ_2	1.229	1.197
	(6.92)***	(6.67)***
ϱ_3	2.809	-
	(13.85)***	-
Chi-square(1)	111.99	9.14
P for equation	0.000	0.003
N	522	522

*p<0.1; ** p<0.05; *** p<0.01 , z-value in parentheses

In both ordered probit models the signs for the biophysical measures were positive and significant. As TSI (SD) increases, the probability of a person choosing higher ranked choices (less clarity) also increases. That is, increases in TSI (SD) lead to lower perceived water clarity. Similarly, an increase in TSI (Chla) leads to a higher perceived greenish tint in the water. Taken together, our ordered probit models do a good job, statistically, linking perceptions to biophysical models.

Using ordered probit results to estimate willingness to pay

Using the results from table 10 we will calculate a probability weighted perceptions measure that is functionally linked to the biophysical measures. The theoretical format for calculating the weighted probability models is the same for the Water Clarity and Water Color functions.

Where the weighted perception can be expressed as:

$$weighted\ perception = \sum_{j=1}^{4} P(j) \cdot \mathrm{j} \tag{26}$$

where *j* is the option chosen in the questionnaire (i.e. one, two, etc.). The table below (table 11) can be helpful in visually understanding how the weighted probability perception is calculated.

Table 11 Example of Probabilities for Bear Lake and Utah Lake

	Bear Lake	**Utah Lake**
TSI(SD)	34.1	79.8
P(1)	15.94%	0.33%
P(2)	31.93%	3.48%
P(3)	45.78%	38.52%
P(4)	6.35%	57.67%
Probability Weighted Clarity Perception	2.43	3.54
Mean Survey Response	2.39	3.65

One can see in table 11 that the mean response and the weighted perception values are very close to each other. Similar results were found for other lakes, so our model appear to be consistent with individuals' perception of water quality. We will use the perceptions model (table 9, column 3) to calculate the number of trips as a function of travel cost, respondent characteristics, with the probability weighted perception value for the lake replacing the raw perception measure. This version of the model allows one to account for the relationship between perception and biophysical measures. We will then estimate WTP based on how changes in biophysical measures can influence the probability weighted perception. Using the standard bootstrapping technique of repeated sampling with replacement we may then examine any statistical differences between WTP calculated using the weighted perception measure and WTP based on the observed perception.

Estimating mean willingness to pay

In this section we will show the results from five different methods of calculating the mean willingness to pay (WTP) for an improvement in water quality for the ten most visited lakes in the dataset. The first two estimates will be based on the models estimated from the truncated negative binomial model (table 9). The next three estimates will be based on the link between biophysical and perception measures. Based on Haab and McConnell (2002), the seasonal welfare measure for the truncated negative binomial model is given by:

$$WTP = \frac{Trip\ 1}{-\beta_{travel\ cost}} \tag{27}$$

where the number of trips (*Trip 1)* can be estimated from table 9, and the denominator is the coefficient of *Travel Cost* (table 9). To measure the change in welfare associated with a change in water quality, one calculates:

$$WTP = \frac{Trip\ 2 - Trip\ 1}{-\beta_{travel\ cost}} \tag{28}$$

where just as in the previous equation, where *Trip 1* is the baseline number of trips, *Trip 2* is the number of trips after water quality improvement, and the denominator is the coefficient of *Travel Cost* (table 9).

Using the coefficients from the truncated negative binomial model based on the biophysical measures (table 9, column 2) we can estimate the number of trips at baseline conditions (Trip 1) where the TSI (SD) values are stated as *Baseline TSI (SD)* on table 12. A second estimate of the number of trips (Trip 2) under a 25% improvement in water quality is then calculated, the mean TSI (SD) for such improvement is stated on table 12 as *Improved TSI (SD)*. After, the willingness to pay associated with the change in water quality for each individual is calculated, we then compute the mean WTP per lake.

Table 12 Mean willingness to pay for 25% improvement in water clarity, biophysical model

Lake	Visitors	Baseline TSI(SD)	Improved TSI(SD)	MWTP after reducing TSI(SD) by 25%
Strawberry Reservoir	47	32.3	24.23	$60.91 (-$102.67 — $224.50)
Bear Lake	62	34.1	25.58	$51.11 (-$81.92 — $184.14)
Flaming Gorge Reservoir	16	36.5	27.38	$50.62 (-$92.46 — $193.70)
East Canyon Reservoir	18	42.5	31.88	$73.83 (-$128.12 — $275.77)
Deer Creek Reservoir	31	42.8	32.1	$91.97 (-$148.36 — $332.30)
Rockport Reservoir	12	43.9	32.93	$90.07 (-$161.07 — $341.21)
Jordanelle Reservoir	19	44.8	33.6	$94.65 (-$168.08 — $357.38)
Pineview Reservoir	41	50.4	37.8	$101.83 (-$150.02 — $353.67)
Willard Bay Reservoir	35	68.8	51.6	$142.32 (-$189.59 — $474.23)
Utah Lake	54	79.8	59.85	$193.45 (-$287.46 — $674.35)

95% confidence bounds stated in parentheses

The 95% confidence interval for WTP is based on 1000 bootstrapped samples from the data. Given the statistical insignificance of the biophysical metrics in the baseline model, the fact that the 95% confidence interval overlap zero is not surprising.

When calculating the WTP for perceptions, the same strategy used in table 12 was again used in table 13. This time we used the coefficients from table 9, column 3, where we estimated the number of trips at baseline conditions (Trip 1), but instead of using the TSI

(SD) values we use the stated perception of water clarity. A second estimate of the number of trips (Trip 2) under perceived improved water quality is then calculated. In order to calculate *Trip 2*, we shifted perception values of clarity by one unit (i.e. if perception of clarity equal to 4 change to 3, from 3 to 2, from 2 to 1; and if perception of clarity is equal to 1, no changes were made). The mean value for improved clarity is stated in table 13 as *Improved Clarity*. Just as in the previous table the change in welfare associated with a change in water quality is calculated, its value is stated in the fifth column. Table 12 and 13 show that MWTP measures differ for water clarity improvements. The WTP point estimates are roughly 3-4 times larger for the perceptions model than the biophysical model.

It is important to note that a 25% reduction in TSI (SD) is not the same as shifting perception of Water Clarity by 1 unit, because without a linking model we cannot correlate how TSI (SD) relates to a shifting in perceived water clarity. Based on a reasonable thought process, it is possible to consider that in a four value increments a shifting by one unit would be close to a change of 25% when compared to a scale that ranges from 0 to 100. Our highest observed TSI (SD) value is 79.8, meaning that an improvement of 25% would change its trophic classification. If the highest TSI (SD) was above 80, then an improvement of 25% would not lead to a change in trophic classification. Based on the lack of certainty of how changes in TSI (SD) shifts 1 unit of clarity, this study uses three different approaches in the linked models. Looking back at tables 12 and 13, it is difficult to choose which one is the better estimate of WTP.

Table 13 Mean willingness to pay for one unit improvement in water clarity, perceptions model

Lake	**Visitors**	**Baseline Clarity**	**Improved Clarity**	**MWTP after shifting perception of Clarity by 1 unit**
Bear Lake	62	2.39	1.56	$170.34 (-$81.57 — $422.25)
Flaming Gorge Reservoir	16	2.44	1.63	$148.71 (-$97.91 — $395.32)
Deer Creek Reservoir	31	2.64	1.77	$230.13 (-$66.93 — $527.19)
Strawberry Reservoir	47	2.65	1.7	$252.19 (-$130.76 — $635.14)
East Canyon Reservoir	18	2.78	1.78	$231.75 (-$78.38 — $541.93)
Jordanelle Reservoir	19	2.89	1.89	$286.14 (-$98.46 — $670.74)
Pineview Reservoir	41	3.00	2.00	$252.80 (-$66.10 — $571.70)
Rockport Reservoir	12	3.08	2.17	$228.48 (-$57.23 — $514.19)
Willard Bay Reservoir	35	3.11	2.14	$283.03 (-$75.66 — $641.72)
Utah Lake	54	3.65	2.65	$292.54 (-$57.61 — $642.69)

95% confidence bounds stated in parentheses

LINKED BIOPHYSICAL TO PERCEPTIONS MODEL

In calculating WTP, we now used the weighted perception probability values created from the ordered probit models (table 10) as a substitute for the “raw” Water Clarity and Water Color perception values in the truncated negative binomial model of perceptions (table 9, column 3). Equation 26 shows how the weighted perception is calculated, where the P (j) change as TSI (SD) changes (equation 24). Any change in TSI (SD) will change the weighted perception probability values; these new values were used to calculate the number of trips at the baseline and improved TSI (SD) values. The standard welfare measure for a Poisson model then applies (equation 28).

Improving water clarity by reducing TSI (SD) by 25%

When our highest TSI(SD) value (79.8) at Utah Lake is reduced by 25%, its new TSI(SD) value would be 59.85. Thus we would expect that the mean perception (*Water Clarity*) value to move from 3.54 to 3.11 (table 14, last row). Similarly, our lowest TSI(SD) value is 32.2 at Strawberry Reservoir; a 25% improvement reduces this to 24.23. Using our linking model, the probability weighted water quality perception moves from 2.37 to 2.14 (table 14, row 2). Calculations are shown for other lakes in table 14.

Table 14 Mean WTP using "Linked biophysical to perception model" reduction in TSI (SD) by 25%

Lake	**Visitors**	**Baseline TSI(SD)**	**Improved TSI(SD)**	**Baseline Weighted Perceptions**	**Improved Weighted Perceptions**	**MWTP after reducing TSI(SD) by 25%**
Strawberry Reservoir	47	32.3	24.23	2.37	2.14	$55.96 (-$23.61 — $135.53)
Bear Lake	62	34.1	25.58	2.42	2.17	$52.27 (-$22.31 — $126.86)
Flaming Gorge Res.	16	36.5	27.38	2.49	2.23	$46.88 (-$28.12 — $121.88)
East Canyon Res.	18	42.5	31.88	2.66	2.36	$64.17 (-$16.66 — $145.02)
Deer Creek Res.	31	42.8	32.1	2.67	2.37	$76.32 (-$19.77 — $172.41)
Rockport Reservoir	12	43.9	32.93	2.70	2.39	$75.51 (-$20.80 — $171.83)
Jordanelle Reservoir	19	44.8	33.6	2.72	2.41	$81.55 (-$21.35 — $184.44)
Pineview Reservoir	41	50.4	37.8	2.87	2.53	$83.90 (-$18.13 — $185.94)
Willard Bay Res.	35	68.8	51.6	3.31	2.91	$105.13 (-$16.94 — $227.20)
Utah Lake	54	79.8	59.85	3.54	3.11	$117.55 (-$17.19 — $252.28)

95% confidence bounds stated in parentheses

Comparing table 14 (columns five and six) to table 13 (columns one and two) we can see that a change of 25% in TSI(SD) does not correspond to the same level of changes when observing the *Improved Clarity* to *Improved Weighted Perception*. While the initial values for clarity and weighted perceptions are relatively close, a 25% change in TSI (SD) does not correspond to a one-unit change in perception when "passed through" the linking model. While the MWTP values of table 14 appear to have the same ratio difference between table 12 and 13, the MWTP values in table 14 are much closer to the values from the biophysical model (table 12). As the MWTP values start to increase, the difference between values of both tables also rises. The confidence interval on table 14 is relatively smaller than that of table 12.

Improving water clarity by reducing TSI (SD) to center value of improved trophic classification

Table 3 shows that the range of TSI values between each trophic classification is not the same so it may be reasonable to believe that reducing TSI (SD) to the middle of the next "better" trophic status would be a reasonable policy goal. For example, if TSI (SD) for a lake is 78 (hypereutrophic), it would change to 60 (eutrophic). Lakes with TSI (SD) values lower than 40 (oligotrophic) would not change. If the TSI (SD) were equal to a value ranging from 40 to 50, the new value would be changed to the mean of our lakes in the oligotrophic trophic classification since the middle level of the oligotrophic trophic classification (20) and is below any values found in the dataset for TSI (SD).

Table 15 Mean WTP using "link biophysical to perception model" change TSI (SD) to center value of improved trophic classification

Lake	**Visitors**	**Baseline TSI(SD)**	**Improved TSI(SD)**	**Baseline Weighted Perceptions**	**Improved Weighted Perceptions**	**MWTP after changing Trophic Classification for TSI(SD)**
Strawberry Reservoir	47	32.3	32.3	2.37	2.37	$ -
Bear Lake	62	34.1	34.1	2.42	2.42	$ -
Flaming Gorge Reservoir	16	36.5	36.5	2.49	2.49	$ -
East Canyon Reservoir	18	42.5	35	2.66	2.45	$44.66 (-$11.29 — $100.61)
Deer Creek Reservoir	31	42.8	35	2.67	2.45	$55.07 (-$13.91 — $124.06)
Rockport Reservoir	12	43.9	35	2.7	2.45	$60.64 (-$16.42 —$137.71)
Jordanelle Reservoir	19	44.8	35	2.72	2.45	$70.97 (-$18.36 — $160.30)
Pineview Reservoir	41	50.4	45	2.87	2.73	$34.43 (-$6.91 — $75.77)
Willard Bay Reservoir	35	68.8	45	3.31	2.73	$152.34 (-$26.51 — $331.20)
Utah Lake	54	79.8	60	3.54	3.11	$116.55 ($-17.01 — 250.10)

95% confidence bounds stated in parentheses

In the previous table we can see that even though we modified the way that changes in TSI (SD) occur, it appears that the improved weighted perceptions (table 15, column 6) is not really close to the improved clarity perception values (table 13, column 4). The first 3 rows of table 15 do not present MWTP since there were no change in their TSI(SD) since those lakes are classified as oligotrophic. Compared to table 12, the values provided on the previous table have a narrower confidence interval, though one should note that the MWTP changes are not uniform since moving to the center value of a better trophic classification can represent different value changes for each lake. For example, Pineview Reservoir had an improvement in TSI(SD) of 5.4 units, while Willard Bay Reservoir had a change of 23.8 units. One may observe that the "larger" change for Willard Bay Reservoir generated a much larger increase in welfare than Pineview Reservoir, even though both reservoirs were moving from "eutrophic" status to "mesotrophic" status. The MWTP for improving Willard Bay Reservoir is over four times as large as the MWTP to improve the quality of Pineview Reservoir.

Improving water clarity by changing TSI (SD) by 1.5 meters

If we observe table 3, we can see that the range of values between each trophic classification is not the same, but on average each of those classifications are roughly 1.5 meters (4.92 feet) apart in measured Secchi depth. We now estimate MWTP for 1.5 meters improvement in clarity.

Table 16 Mean WTP using "link biophysical measure to perception" based on change in meters

Lake	Visitors	Baseline TSI(SD)	Improved TSI(SD)	Baseline Weighted Perceptions	Improved Weighted Perceptions	MWTP after improving water clarity by 1.5 meters
Strawberry Reservoir	47	32.3	29.42	2.37	2.29	$19.74 (-$8.12 — $47.60)
Bear Lake	62	34.1	30.87	2.42	2.33	$19.46 (-$8.10 — $47.01)
Flaming Gorge Reservoir	16	36.5	32.75	2.49	2.39	$18.80 (-$11.06 — $48.67)
East Canyon Reservoir	18	42.5	37.17	2.66	2.51	$31.37 (-$7.78 — $70.52)
Deer Creek Reservoir	31	42.8	37.4	2.67	2.52	$37.72 (-$9.33 — $84.78)
Rockport Reservoir	12	43.9	38.13	2.7	2.54	$38.69 (-$10.21 — $87.60)
Jordanelle Reservoir	19	44.8	38.73	2.72	2.56	$43.10 (-$10.80 — $96.98)
Pineview Reservoir	41	50.4	42.15	2.87	2.65	$53.54 (-$11.07 — $118.15)
Willard Bay Reservoir	35	68.8	49.69	3.31	2.86	$118.32 (-$19.49 — $256.13)
Utah Lake	54	79.8	51.9	3.54	2.91	$175.48 (-$28.24 — $379.20)

95% confidence bounds stated in parentheses

Just as in table 14 and 15, table 16 confidence interval is narrower than that of table 12. It appears that table 16 MWTP values appears to get approach the values in table 12 as MWTP increases. Just as in table 14, MWTP values rises as one goes down the rows in table, this can be attributed to the fact that constant level changes give the impression of higher improvements in “dirtier” lakes when compared to cleaner lakes After using the last approach where Secchi depth was changed by 1.5 meters, a visual examination appears to show that none of the three models fully captures how a change in biophysical measure would correspond to unit change in the perception model. In order to fully understand whether any of those models are close to explaining such changes we will use the convolution method. Using the perception model and each of the three linked models, we estimated new WTP distributions using standard bootstrapping techniques of repeated sampling with replacement. Based on Poe, Giraud, and Loomis (2005), we use the convolution method by calculating various sampling schemes of the difference $X_i - Y_{zj}$, where X is the WTP distribution of the perception model and Y is the WTP distribution for the linked model, where the indicator z would designate which of the three models would be used (change by 25%; change to the middle of trophic classification; change in meters). The significance of the differences is computed by the number of negative values as a proportion of all paired differences. The null hypothesis is that the difference between the distributions is equal to 0. The model related to change in TSI (SD) by 25% was the only model where the null hypothesis was not rejected at the 5% confidence level, its value was 0.080. The models related to change in trophic classification and change in meters and had the respective 0.041 and a 0.047 level of significance. The table below exemplifies the results of the test.

Table 17 Comparison of WTP distributions of weighted models to WTP distribution of baseline perceptions model

Linked Model	Test Statistic	Different WTP Distribution
Reduce TSI(SD) by 25%	0.08	No
Reduce TSI(SD) to center of trophic classification	0.04	Yes
Reduce TSI(SD) based on 1.5 meters improvement in Sight depth	0.05	Yes

Since the linked model where the TSI (SD) is reduced by 25% can also be directly compared to the distribution of our baseline biophysical model we also compared such distribution. Its value was 0.43, meaning that we could not rejected the null hypothesis that the distributions are different from each other.

CONCLUSION

In this study we have attempted to understand changes in trip behavior by exploring the relationship between the biophysical measures of water quality and people's perception of water quality. Water quality in travel cost models have generally been estimated in one of two ways: Using biophysical measures or using perceived water quality. The first approach requires the analyst to assume that biophysical measures can be perceived by the respondent, and the second presumes that a measure of perceived water quality can be 'translated' back to some metric that is useful to the natural scientists. What is missing is the link between biophysical and perceived measures of water quality, and how changes in biophysical measures relate to a person's perception of water quality. Further, the two approaches for including water quality in a travel cost model could lead to different models and thus, different welfare estimates associated with changes in water quality.

Using the knowledge that water clarity is related to TSI (Secchi depth), and that TSI (Chlorophyll) accounts for the greenish tint in the water, simple models that link perceptions and biophysical measures were estimated. We used the "linkage" models three different ways: (i) postulating a fixed percentage change in the biophysical measures, (ii) postulating fixed change of 1.5 meters in Secchi depth measure (improved water clarity) at all lakes, (iii) postulating an improvement to the next best level of quality, where the improvement was to the mid-point of the next best trophic classification. After calculating all three different ways of changing biophysical measures, we used the convolution method to understand the difference between the distribution of WTP estimated with the original perceptions model and the three estimates that account for the link between biophysical and perception measures. The model using the percentage levels [approach (i)] was the only model where the null hypothesis that the difference between WTP distributions was equal to zero was not rejected. The same approach (i) was also compared with the original biophysical model WTP distribution the null hypothesis again was not rejected.

Future studies should focus on a closer examination of the model linking biophysical and perception measures. Increasing the sample size would be beneficial to understanding overall perception levels. Some lakes in the data only had a unique visitor or a couple visitors. While this is not enough to remove such individuals from our sample, increasing the sample size would help to create a more representative model of perceptions across a broader variety of lakes. Further, the different preferences and activities of people, as revealed by different primary activities, may affect perceptions of water quality. Our linkage models did not investigate this possibility. The implication is that if a certain lake is being used primarily for warm water fishing and the anglers are interested in a certain variety of fish, the water quality level desired may be different than when compared to swimmers or boaters.

Even though the results did not show a perfect link when using the convolutions model, this paper shows that such a link should be analyzed. The use of a large dataset would be beneficial to better understand such a link and in identifying the prospective differences between lakes and groups visiting the lakes. Different levels of water quality may be preferred by different groups. Finally this paper raises the question of whether regulators should focus on maintaining the water quality level desired based on primary activity of lake or improving all lakes to the same water quality level.

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APPENDIX

Appendix 1

Lake Name	**TSI(SD)**	**TSI(Chla)**	**Mean Clarity**	**Mean Shades of Green**	**Number of Visitors**
Fish Lake	32.11	23.62	2.75	2.00	4
Strawberry Reservoir	32.31	34.34	2.66	2.38	47
Bear Lake	34.10	23.60	2.39	1.68	62
Marsh Lake	36.44	32.25	1.00	2.00	1
Flaming Gorge Reservoir	36.49	34.47	2.44	1.81	16
Duck Fork Reservoir	37.40	23.80	1.00	1.00	1
Tony Grove Reservoir	37.68	31.85	2.00	1.50	2
Huntington Reservoir	38.46	27.45	2.00	2.00	1
Lyman Lake	38.78	28.54	2.33	1.33	3
Tropic Reservoir	39.34	21.57	2.00	2.00	1
Porcupine Reservoir	40.15	32.92	2.60	1.60	5
Silver Lake Flat	40.69	27.14	2.75	2.25	4
Starvation Reservoir	41.02	35.11	2.75	1.75	4
Mantua Reservoir	41.51	40.80	2.78	2.44	9
Navajo Lake	41.53	24.74	2.14	2.14	7
Tibble Fork Reservoir	42.08	20.06	3.11	2.33	9
Mirror Lake	42.11	32.04	2.00	1.80	5
Whitney Reservoir	42.50	31.92	3.00	1.50	2
East Canyon Reservoir	42.51	34.90	2.78	2.11	18
Joes Valley Reservoir	42.61	23.32	1.00	3.00	1
Deer Creek Reservoir	42.84	43.69	2.65	2.06	31
Quail Creek Reservoir	43.06	21.61	2.56	2.11	9
Causey Reservoir	43.51	26.24	3.00	3.00	3
Scout Lake	43.64	27.26	1.00	2.00	1
Moon Lake	43.70	42.61	3.00	2.00	1
Big Sand Wash Reservoir	43.71	27.20	3.00	2.00	1
Rockport Reservoir	43.91	39.49	3.08	2.17	12
Currant Creek Reservoir	44.01	27.90	2.67	2.67	3
Jordanelle Reservoir	44.82	38.09	2.89	2.26	19
Washington Lake	45.25	29.07	2.75	2.00	4
Smith and Morehouse Reservoir	45.49	29.44	2.25	1.75	4
Sand Hollow	45.58	25.59	1.50	1.50	4
Woodruff Creek Reservoir	45.79	39.67	4.00	2.00	1

Trial Lake	46.04	29.95	1.67	1.67	3
Panguitch Lake	46.11	49.72	2.50	2.00	4
Kens Lake	46.69	30.57	2.50	2.00	2
Puffer Lake	46.75	40.08	3.00	2.00	1
Wall Lake	47.15	27.16	3.00	2.00	1
Huntington Lake North	47.31	19.77	4.00	1.00	1
LaBaron Reservoir	47.74	39.77	3.00	3.00	1
Scofield Reservoir	47.77	68.01	2.17	2.00	6
Echo Reservoir	47.98	41.01	3.00	1.89	9
Mill Hollow Reservoir	48.19	45.95	3.00	2.00	1
Bridger Lake	48.21	46.56	3.50	2.00	2
Butterfly Lake	48.25	37.24	2.00	2.00	1
Blanding City Reservoir	48.96	27.19	2.00	2.00	2
Yankee Meadow Reservoir	49.23	48.84	1.50	1.50	2
Settlement Canyon Reservoir	49.81	38.54	3.00	1.50	4
Spirit Lake	49.90	40.59	3.00	2.00	1
Pelican Lake	50.25	40.84	2.00	2.50	2
Lower Gooseberry Reservoir	50.39	38.29	3.00	2.00	1
Pineview Reservoir	50.40	40.89	3.00	2.00	41
Birch Creek Reservoir	50.76	44.59	3.00	2.00	1
Red Fleet Reservoir	50.91	35.43	2.00	2.00	2
Hyrum Reservoir	51.58	39.94	3.10	2.10	10
Gunlock Reservoir	52.47	38.53	3.00	1.75	4
Piute Reservoir	52.49	40.34	2.50	2.00	2
East Park Reservoir	52.92	32.92	3.00	2.00	1
Upper Enterprise Reservoir	53.74	51.12	2.00	1.50	2
Palisades Lake	53.99	32.79	2.80	2.40	5
Matt Warner Reservoir	54.64	58.96	3.00	2.00	1
Newcastle Reservoir	54.69	55.84	3.00	3.00	1
Payson Lake	55.01	44.48	3.00	2.00	4
Grantsville Reservoir	55.54	37.31	4.00	3.00	1
Baker dam reservoir	56.51	57.54	3.00	2.00	1
Kents Lake	59.28	50.94	2.00	2.00	1
Salem Pond	60.28	61.94	3.00	3.00	1
Gunnison Reservoir	61.07	32.93	3.00	3.00	1
Newton Reservoir	62.64	52.18	3.33	2.00	3
Yuba	63.54	45.19	3.67	2.00	3
Otter Creek Reservoir	65.52	47.59	3.00	2.33	3
Willard Bay Reservoir	68.78	42.12	3.11	2.17	35

Mona Reservoir	76.78	50.70	2.00	2.00	1
Gunnison Bend Reservoir	78.43	26.51	4.00	2.00	3
Cutler Reservoir	78.74	60.15	4.00	1.50	2
Utah Lake	79.81	60.82	3.65	2.24	54
Fish Lake	32.11	23.62	2.75	2.00	4
Strawberry Reservoir	32.31	34.34	2.66	2.38	47
Bear Lake	34.10	23.60	2.39	1.68	62
Marsh Lake	36.44	32.25	1.00	2.00	1
Flaming Gorge Reservoir	36.49	34.47	2.44	1.81	16
Duck Fork Reservoir	37.40	23.80	1.00	1.00	1